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Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review

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ABSTRACT

In recent years there has been a growing attention towards use of solar energy. The main advantages of photovoltaic (PV) systems employed for harnessing solar energy are lack of greenhouse gas emission, low maintenance costs, fewer limitations with regard to site of installation and absence of mechanical noise arising from moving parts. However, PV systems suffer from relatively low conversion efficiency. Therefore, maximum power point tracking (MPPT) for the solar array is essential in a PV system. The nonlinear behavior of PV systems as well as variations of the maximum power point with solar irradiance level and temperature complicates the tracking of the maximum power point. A variety of MPPT methods have been proposed and implemented. This review paper introduces a classification scheme for MPPT methods based on three categories: offline, online and hybrid methods. This classification, which can provide a convenient reference for future work in PV power generation, is based on the manner in which the control signal is generated and the PV power system behavior as it approaches steady state conditions. Some of the methods from each class are simulated in Matlab/Simulink environment in order to compare their performance. Furthermore, different MPPT methods are discussed in terms of the dynamic response of the PV system to variations in temperature and irradiance, attainable efficiency, and implementation considerations.

Contents

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1. Introduction

The continuous increase in the level of greenhouse gas emissions and the climb in fuel prices are the main driving forces behind efforts to utilize various sources of renewable energy [1,2]. Among renewable sources of energy, solar energy constitutes a suitable choice for a variety of applications mainly due to the possibility of direct conversion of this form of energy to electrical energy using PV systems. Nevertheless, utilizing PV systems as an alternative source of energy requires a substantial amount of investment. In order to reduce the overall cost of PV systems, therefore, extraction of the maximum power from a solar cell turns out to be a vital consideration for optimal system design. At the appropriate operating point for a solar cell, assuming a given cell efficiency, the maximum output power depends on the radiation intensity, ambient temperature and load impedance. There is a single operating point enabling attainment of maximum power, tracking of which through variations in radiation intensity and temperature is essential in order to ensure the efficient operation of the solar cell array (Fig. 1). The fundamental problem addressed by MPPT is to automatically determine the PV output voltage or output current for which the PV array produces maximum output power under a given temperature and irradiance. Attainment of maximum power involves load-line adjustment under variations in irradiation level and temperature.

The maximum power point tracking, MPPT not only enables an increase in the power delivered from the PV module to the load, but also enhances the operating lifetime of the PV system [3]. A variety of MPPT methods have been developed and implemented [4,5]. These method can be differentiated based on various features including the types of sensors required, convergence speed, cost, range of effectiveness, implementation hardware requirements, popularity [5].

In essence, however, different MPPT methods can be categorized offline methods, which are dependent on solar cell models, online methods which do not specifically rely on modeling of the solar cell behavior, and hybrid methods which are a combination of the aforementioned methods. The offline and online methods can also be referred to as the model-based and model-free methods, respectively.

Offline methods generally require to one or more of the solar panel values, such as the open circuit voltage (V_{OC}), short circuit current (I_{SC}), temperature and irradiation. These values are employed to generate the control signal necessary for driving the solar cell to its maximum power point (MPP). In the course of the tracking operation, this control signal remains constant if ambient conditions can be regarded as fixed and there are no attempts to regulate the output power of the PV system.

In online methods, usually the instantaneous values of the PV output voltage or current are used to generate the control signals. The control signal is applied to the PV system along with a small methodical and premeditated perturbation in voltage or current or duty cycle (control signal) and the resulting output power is determined. By analyzing response of perturbation on output power of PV panel, the direction of change (decrease or increase) of the control signal is determined. Hence, unlike offline methods, with a perturbation applied, the control signal can no longer be regarded as constant. Therefore, tracking the maximum output power involves oscillations around the optimum value.

In hybrid methods that represent a combination of the offline and online methods, tracking of the MPP is performed in two steps: estimation and exact regulation of MPP. The First step, which involves estimation of MPP, relies on offline methods to place the set point close to MPP. The second step, which can be regarded as a fine-tuning step, is based on online methods and attempts to reach the actual value of MPP.

In this review, different MPPT techniques employed in PV systems are categorized according to a novel classification scheme as offline methods, online methods, or hybrid methods. In particular, the given method is identified as offline if they are depended on the physical data model of the solar cells to track the maximum power point. If an MPPT method does not rely on a model, but instead employs measured instantaneous values of PV output current and output voltage in order to track MPP with higher accuracy, it is referred to as an online method. Finally, MPPT methods which combine the offline and online approaches are grouped under hybrid MPPT methods based on the proposed classification scheme. Furthermore, in order to facilitate selection of MPPT algorithms, the MPPT methods presented are compared based on simulation of PV systems. In order to assess MPPT techniques including the offline, online and hybrid methods using simulations, the solar cell is modeled in an environment including the converter and load. The remainder of this work is organized as follows: PV systems and PV panel models are introduced in Section 2. In Section 3, important MPPT algorithms are described under the three categories of offline methods, online methods and hybrid methods. In Section 4, different methods will be discussed in terms of their efficiency, their overall implementation scheme, the sensors required for their implementation and the associated costs. A table summarizing the major features associated with each method will also be provided.

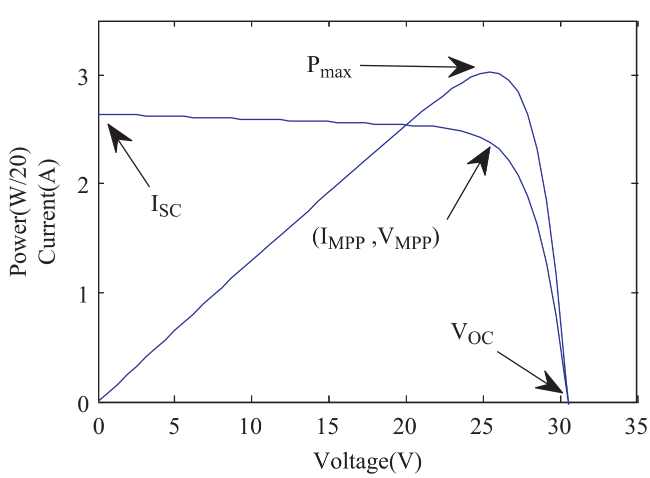

Fig. 1. *I–V* and *P–V* characteristics of solar cell.

2. System overview

PV systems consist of solar panels, DC–DC voltage converters, controllers and batteries. DC–DC voltage converters are used for matching the characteristics of the load with those of the solar panels. DC–DC voltage converters are classified into three categories, namely boost converters, buck converters and buck-boost converters. Selection of the type of DC–DC voltage converter depends on the voltage levels involved. The use of the battery allows the photovoltaic system to behave as a real source to the

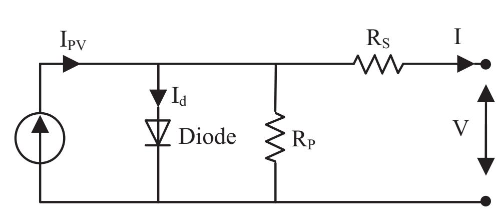

Fig. 2. Equivalent circuit of solar panel.

feeder so that it may exhibit constant voltage levels corresponding to different loads. The battery is also required for saving power as well as temporary compensation for power variations. The mathematical models of the PV panel are briefly described below.

Fig. 2 shows the equivalent circuit of a solar panel. A solar panel is composed of several photovoltaic cells employing series or parallel or series–parallel external connections. Eq. (1) describes the I–V characteristic of a solar panel [6].

$$I = I_{PV} - I_O\left[\exp\left(\frac{V+R_S I}{aV_t}\right)-1\right]-\frac{V+R_S I}{R_P} \tag{1}$$

where, I_{PV} is the PV current, I_o is the saturated reverse current, "a" is a constant known as the diode ideality factor, $V_t = N_s KT/q$ is the thermal voltage associated with the cells, N_S is the number of cells connected in series, q is the charge of the electron, K is the Boltzmann constant, T is the absolute temperature of the p–n junction, and R_S and R_P are the series and parallel equivalent resistances of the solar panel respectively. I_{PV} has a linear relationship with light intensity and also varies with temperature variations. I_o is dependent on temperature variations. Values of I_{PV} and I_o are calculated from the following equations:

$$I_{PV} = \left(I_{PV,n} + K_I \Delta T\right)\frac{G}{G_n} \tag{2}$$

$$I_O = \frac{I_{SC,n} + K_I \Delta T}{\exp\left(V_{OC,n} + K_V \Delta T\right)/aV_t - 1} \tag{3}$$

In which $I_{PV,n}$, $I_{SC,n}$ and $V_{OC,n}$ are the PV current, short circuit current and open circuit voltage respectively under standard conditions ($T_n = 25\ ^\circ$C and $G_n = 1000\ \mathrm{W/m^2}$). K_I is the coefficient of short-circuit current variation with temperature, $\Delta T = T - T_n$ is the deviation from standard temperature, G the light intensity and K_V is the ratio of the open circuit voltage to temperature.

3. MPPT methods

A major disadvantage of the PV systems is the relatively higher cost required for generation of energy as compared to that produced by conventional power generation systems or even as compared to other renewable sources such as wind power. Therefore, maximizing the efficiency of power delivered to the output by tracking the maximum power point is critical for optimal operation of the PV systems. The PV system is connected to the grid via DC–DC converters. In order to achieve MPPT in PV systems the PV terminal voltage (or current) can be regulated by applying a control signal to the converters. In order to attain MPPT a wide variety of algorithms have been proposed and implemented. In this manuscript, these methods have been classified into three broad categories: offline methods, online methods, and hybrid methods.

3.1. *Offline methods*

In offline methods, also known as model-base methods, usually the physical values of the PV panel are used to generate the control signals. These methods that only are used for PV systems are open circuit voltage method (OCV), short circuit current method (SCC) as well as the MPPT method based on artificial intelligence (AI).

3.1.1. *Open circuit voltage (OCV) method*

This method is one of the simplest offline methods [7–11], which uses the approximately linear relationship between the open circuit voltage (V_{OC}) and the maximum power point voltage (V_{MPP}) under different environmental conditions as described by the following equation:

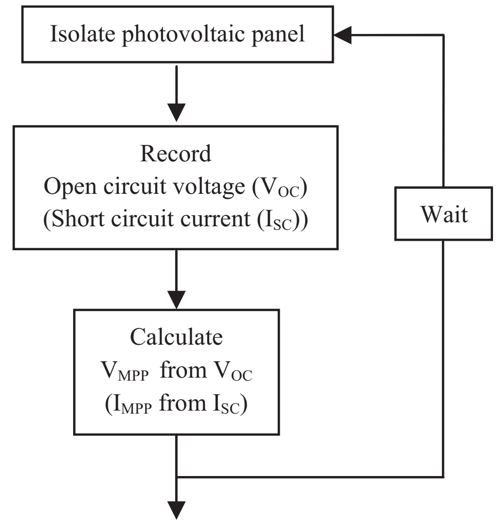

Fig. 3. Flowchart of open-circuit voltage (short-current circuit) method.

$$V_{MPP} \approx KV_{OC} \tag{4}$$

where, K is a constant, which depends on the solar cell characteristics. This constant is empirically derived based on measurement of the V_{OC} and V_{MPP} under different environmental conditions. It is difficult to choose an optimal value for the constant K, however values for this parameter ranging from 0.73 to 0.80 have been reported in polycrystalline PV modules [7,8]. From Eq. (4) V_{MPP} is determined following each measurement of the V_{OC}. In each successive stage as MPP is tracked, this value of V_{MPP} which is chosen as the set point is assumed to remain relatively constant over a wide range of temperature and irradiance values. A flowchart illustrating this method is shown in Fig. 3. In spite of the relative ease in implementation and low costs, this method suffers from two major disadvantages. First, the MPP may not be tracked accurately. Second, measurement of V_{OC} requires periodic shedding of the load, which may interfere with circuit operation and will cause more power losses. To prevent this loss of power, pilot cells have been used to obtain V_{OC} [12,13]. These pilot cells must be carefully chosen so that the characteristics of the PV array are represented realistically. To overcome power losses associated with load interruption, a more straightforward but approximate approach can be proposed. This approach involves measurement of the temperature and irradiance and estimation of the V_{OC} based on the governing model equations.

3.1.2. *Short circuit current method (SCC)*

This method represents another offline approach [14–18] which is relatively similar to the OCV method (Fig. 3). There is also an approximately linear relationship between the short circuit current (I_{SC}) of the solar panel and the MPP current (I_{MPP}), which can be described by the following equation:

$$I_{MPP} \approx KI_{SC} \tag{5}$$

where, K is a constant between 0.8 and 0.9. Similar to the OCV method, the load should be shed in order to determine the I_{SC}. While the SCC method is more accurate and efficient than the OCV method [17], due to practical issues associated with measuring the I_{SC}, its implementation costs are higher. In [18], a boost converter is used, where the switch in the converter itself can be used to apply a short circuit to the PV array. An improvement similar to that proposed above for the OCV method can be applied to the SCC method. In particular, power losses associated with

load interruption can be avoided if measurement of the temperature and irradiance is employed to estimate the SCC based on the governing model equations. As pointed out above, however, there is a trade-off involving accuracy associated with the proposed improvement.

OCV and SCC methods fail to deliver maximum output power to the load for two reasons. The first reason is load interruption occurring during measurement of I_{SC} or V_{OC}, and the second reason is that MPP can never be tracked quite exactly using these method in the first place as suggested by Eqs. (5) or (4). These two methods cannot be categorized as 'true seeking' MPP methods, however, the simplicity of these algorithms and the ease with which they can be implemented make them suitable for use as part of novel hybrid methods [19,20].

3.1.3. Artificial intelligence

Artificial intelligence (AI) techniques are becoming popular as alternative approaches to conventional techniques or as components of integrated systems. They have been used to solve complicated practical problems in various areas. While AI consists of several disciplines, in this paper only applications of artificial neural networks (ANNs) and fuzzy logic (FL) are considered. In recent years, methods based on ANNs [21–26] and FL [27–34] have been successfully employed for implementation of MPP searching

3.1.3.1. Artificial neural networks method (ANN). An ANN is a collection of electrical neurons (Fig. 4) connected based on various topologies. The most common application of an ANN involves identification and modeling of the system using nonlinear and complex functions. During the learning process in ANNs, the Weights (W_i) are determined. The ANN undergoes an adaptation cycle, during which the weights are updated until the network reaches a state of equilibrium.

In order to accurately identify the MPP using ANN's the W_i has to be determined appropriately based on the relationship between the input and the output of the PV system. Therefore, the PV array is tested over months or years and the pattern between the input and output of the neural network are recorded.

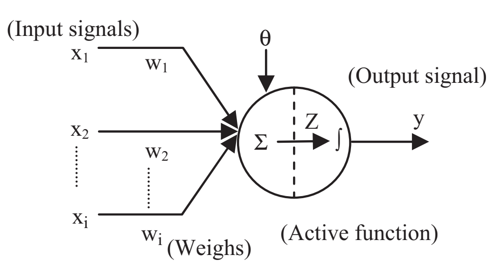

Fig. 4. The basic neuron.

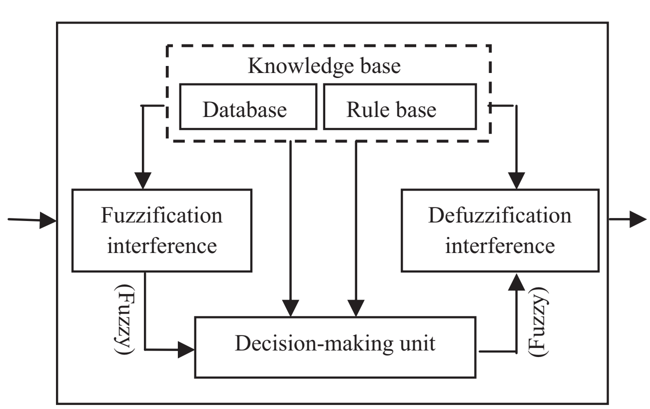

Fig. 5. Flow diagram of fuzzy inference system.

The input signal to each neuron is either the signal received from neighboring neurons or the ANN input variables associated from the nonlinear system under study. In application of ANNs to MPPT, the input variables can be PV array parameters like V_{OC} and I_{SC}, atmospheric data like irradiance and temperature, or any combination of these. The output of ANN is usually one of several reference signals, the most common of which is the duty cycle signal used to drive the power converter to operate at or close to the MPP.

Hiyama et al. were the first to propose use if ANN for MPPT [21]. In their method, V_{OC} served as the only input to the ANNs originating from the solar panel. The output of the ANNs is a signal which can be compared with the instantaneous voltage in order to generate the control signal needed to drive the solar panel to MPP through a PI controller.

The advantage of the ANN-based method lies in the fact that the trained neural network can provide a sufficiently accurate MPPT without requiring extensive knowledge about the PV parameters. However, it must be noted that since most PV arrays exhibit different output characteristics, an ANN has to be specifically trained for the PV array with which it will be used. The characteristics of a PV array are also time-varying, which implies that the neural network has to be periodically trained to guarantee accurate tracking of MPP. In order to implement periodical training, new data has to be collected, which is a time-consuming process.

3.1.3.2. Fuzzy logic method (FL). Fig. 5 shows the flow diagram for fuzzy inference system. This system implements the fuzzy logic control in three stages: fuzzification, decision-making, and defuzzification. During fuzzification, crisp input variables are converted into linguistic variables based on a membership function as depicted in Fig. 6.

In the decision-making stage, the rules which are specified by a set of IF–THEN statements define the controller behavior. The rules describing this stage of operation are expressed as linguistic variables represented by fuzzy sets.

In the defuzzification stage, the fuzzy logic controller output is converted from a linguistic variable to a numerical variable still using a membership function as depicted in Fig. 6. This provides an analog signal that will control the power converter and drive the operating point to the MPP.

The fuzzy logic controller inputs are usually an error E and a change in error, E associated with several different variables. In particular, in order to track MPP, the error is computed based on irradiance and temperature [32] or instantaneous values such as power and voltage [33]. The output signal is either the duty cycle itself, or V_{MPP} and I_{MPP} from which the duty cycle can be generated.

Fuzzy logic controllers offer the following advantages: capability of working with imprecise inputs, lack of requirement of

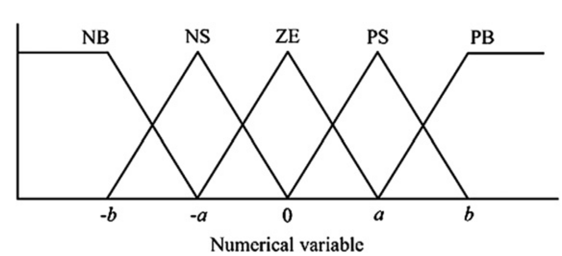

Fig. 6. Membership function for inputs and output of fuzzy logic controller.

an accurate mathematical model, ability to handle nonlinearity, fast convergence. However, the learning ability and accuracy achieved by the approximation depend on the number of the fuzzy levels and the form of the membership functions. In most fuzzy systems, the membership function associated with fuzzification and defuzzification, as well as the antecedent and the consequent fuzzy rules are determined based on trial and error, which can be time-consuming.

3.2. Online methods

In online methods, also known as model-free methods, usually the instantaneous values of the PV output voltage or current are used to generate the control signals. The online methods Perturbation and observation method (P&O), extremum seeking control method (ESC) and as well as the incremental conductance method (IncCond) will be reviewed in this work.

3.2.1. Perturbation and observation method (P&O)

This method is one of the simplest online methods which, has been considered by a number of researchers [35–42]. P&O can be implemented by applying perturbations to the reference voltage or the reference current signal of the solar panel. A flowchart illustrating this method, which is also known as the 'hill climbing method' [43,44], is depicted in Fig. 7, where "X" is the reference signal. In this algorithm, if the reference signal, X is taken as the voltage, (i.e., $X=V$), the goal will involve pushing the reference voltage signal towards V_{MPP} thereby causing the instantaneous voltage to track the V_{MPP}. As a result the output power will approach MPP. To this end, a small but constant perturbation is applied to the solar panel voltage.

The solar panel voltage is changed by applying a series of small and constant perturbations denoted by ($C=\Delta V$) on a step-by-step basis in order to change the system operating point. Following each perturbation, the output power variation (ΔP) is measured. If ΔP is positive, power will approach MPP, therefore a voltage perturbation of the same sign must be applied in the following stage. A negative ΔP, on the other hand, implies that power has moved away from MPP, and a perturbation of opposite sign will have to be applied. This process is repeated until the MPP is reached.

In [45,46] the P&O method has been improved by a novel algorithm to reduce costs. In order to track MPP, this method uses the PV panel current (I_{PV}) as the measured variable for calculation of duty cycle (D), which serves as the reference signal (X).

The P&O method has two main disadvantages. First, in this algorithm the amplitude of the perturbations applied to the system is the main factor determining the amplitude of oscillations as well as the convergence rate of the output power to the MPP. The larger the perturbations the faster the algorithm will find the MPP. Nevertheless a larger perturbation will lead to a higher value of oscillation amplitude. If the applied perturbations are too small, on the other hand, the oscillations around the MPP will be reduced, but the rate of convergence will decrease as well. In other words, in this algorithm there is a trade-off between the rate of response and the amount of oscillations under steady state conditions. To overcome this disadvantage, use of a variable perturbation size that gets smaller as MPP is approached was proposed [47]. In this approach large perturbations are applied when the output power is far from the MPP, whereas smaller steps are adopted as the output power oscillates around the MPP. The magnitude of the variable perturbation is determined based on the slope of the power–current curve. Determination of this slope, however, increases the complexity and cost associated with this approach.

Second, if the system operating point changes quickly, the algorithm will be prone to tracking errors. To address this problem, different methods have been presented [48,49].

3.2.2. Extremum seeking control method (ESC)

Recently, Krstic et al. [50,51] presented a systematic ECS methodology supported by rigorous theories such as averaging and singular perturbation. This real-time optimization methodology involves a nonlinear dynamic system with adaptive feedback. This ESC method has been successfully applied in various systems such as traction maximization in antilock braking for a car [52], power reduction maximization of a flight [53], pressure rise maximization of an aero engine compressor [54], autonomous vehicle target tracking [55], and PID tuning [56]. This method has also been specifically adapted for PV systems in order to track MPP [57–60].

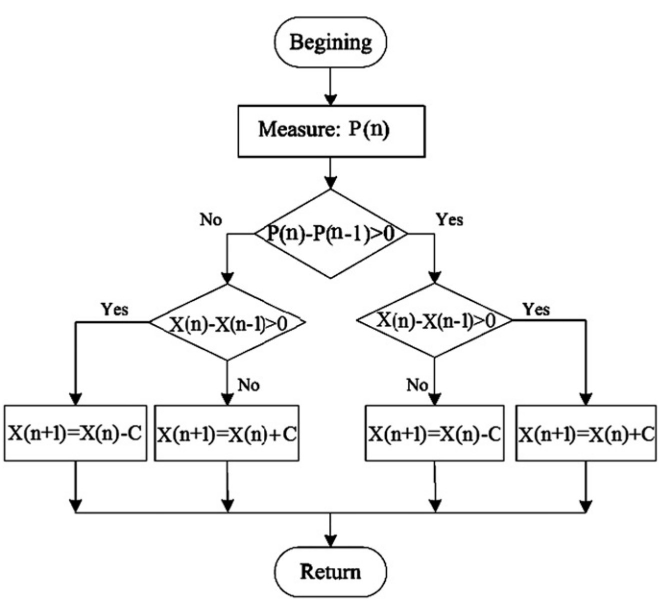

Fig. 7. Perturbation and observation algorithm.

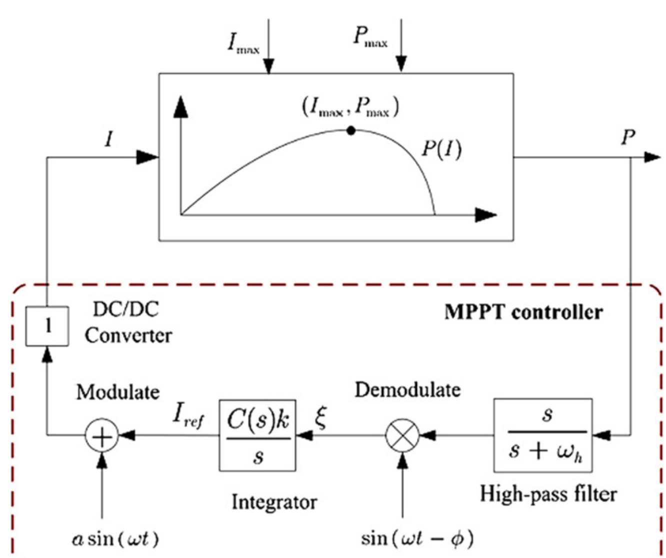

Fig. 8. MPPT controller scheme for the PV system.

With the self-optimizing extremum algorithm as the MPPT controller, the control objective is for the PV system operating point to rapidly trace the MPPs subject to uncertainties and disturbances from the PV panel and the external load.

Fig. 8 shows a block diagram depicting the ESC method implemented in a PV system. In this figure I_{ref} is the initial value of the unknown MPP current, I_{max}, represents the current at which the PV produces maximum power P_{max}, 'a', 'ω' and 'φ' are the amplitude, frequency and phase shift of the sinusoidal perturbation signal, respectively, 'ωh' is the cut-off frequency of the high-pass filter, 'k' is the positive adaptive gain of the integrator, and C(s) represents the transfer function for the compensator.

Suppose a small sinusoidal current represented by $\Delta I = a\sin(wt)$ is added as a perturbation to the reference current (I_{ref}). This leads to the appearance of a ripple power (ΔP), whose phase and amplitude are dependent on the relative location of the operating point relative to the MPP. As shown in Fig. 8, the sinusoidal current perturbation will be added to the reference current, and applied to the PV system. If the resulting ripple in the current is in phase with the output power ripple, the output power will fall to the left of MPP, and the reference current will be less than I_{MPP}, therefore the controller will increase the reference current. If, on the other hand, the ripple in the current is out of phase with that in the output power, the output power will fall to the right of MPP, and the reference current will be larger than I_{MPP}. The controller will, therefore, decrease the reference current until MPP is reached. By passing the output through a high-pass filter, the ripple power (ΔP) can be extracted. The ripple power is then demodulated through multiplication by $\sin(wt-\varphi)$. The resulting signal, zeta is either positive or negative depending on the position in the power output curve. Zeta is then applied to an integrator to modify the I_{ref} value in order to reach MPP. In the case where the operating point falls on MPP, the amplitude of the ripple will be very small and the frequency of the output power ripple will be twice that of the current ripple.

Another MPPT method, which like the ESC method, makes use of the ripple in power to perform the tracking of MPP, is known as the ripple correlation control (RCC) [61]. When a PV array is connected to a power converter, the switching action of the power converter imposes voltage and current ripples on the PV array. As a consequence, the PV array power also becomes subject to ripple. In the RCC method a correlation is performed between the time derivative of the PV array power (dp/dt) and the derivative of the current (di/dt) or voltage (dv/dt) associated with the PV array in an attempt to reach the MPP by driving the power gradient to zero.

The ESC approach has two main advantages. First, the optimization problem involving power maximization is explicitly solved by using the dynamic adaptation-based feedback control law for a sinusoidal perturbation. Attainment of MPP is, hence, guaranteed when the control algorithm is convergent. Second, this approach does not require any parameterization or structural formalization of the modeling uncertainty. The disadvantage of the ESC method lies in the complexity associated with its implementation as well as the necessity to evaluate signals of relatively low amplitude.

3.2.3. Incremental conductance method (IncCond)

The incremental conductance (IncCond) method employs the slope of the PV array power characteristics to track MPP [62–68]. This method is based on the fact that the slope of the PV array power curve is zero at the MPP, positive for values of output power smaller than MPP, and negative for values of the output power greater than MPP.

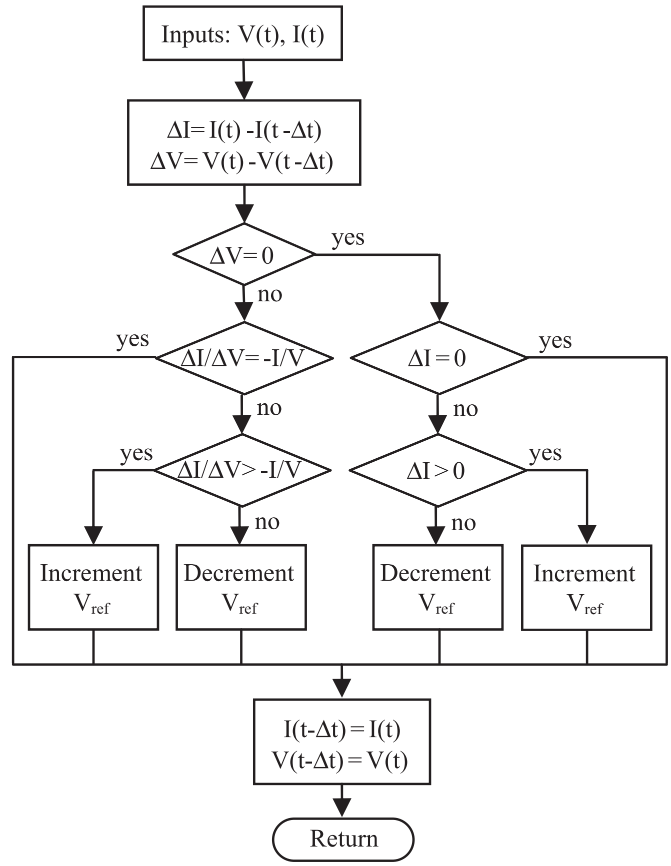

Fig. 9. IncCond algorithm.

The maximum output power, $P_{MPP}=V_{MPP}I_{MPP}$, is obtained by differentiating the PV output power with respect to voltage and setting the result to zero:

$$dP/dV = I + V dI/dV = 0 \tag{6}$$

This leads to:

$$dI/dV \cong \Delta I/\Delta V = -I_{MPP}/V_{MPP} \tag{7}$$

Therefore, by evaluating the derivative one can test whether the PV generator is operating at or near MPP or far away from it.

$$\begin{cases} dP/dV = 0 \\ dP/dV > 0 \\ dP/dV < 0 \end{cases} \rightarrow \begin{cases} \Delta I/\Delta V = -I/V & \text{at MPP} \\ \Delta I/\Delta V > -I/V & \text{left of MPP} \\ \Delta I/\Delta V < -I/V & \text{right of MPP} \end{cases} \tag{8}$$

The MPP can thus be tracked by comparing the instantaneous conductance (I/V) to the incremental conductance (I/V) as shown in the flowchart given in Fig. 9. In Fig. 9 V_{ref} is the reference voltage at which the PV array is forced to operate. At the MPP, V_{ref} equals to V_{MPP}. Once the MPP is reached, the operation of the PV array is maintained at this point unless a change in current, I, occurs as a result of a change in atmospheric conditions leading to a variation in MPP. The algorithm, then, tracks the MPP by applying decrements or increments to V_{ref}. The size of the increment or decrement determines how fast the MPP is tracked. Fast tracking can be achieved by applying larger increments, but the system may not operate exactly at the MPP and oscillations around the MPP may result. That is, use of the IncCond method involves a trade-off between speed of convergence and the likelihood of appearance of oscillations around the MPP.

The main advantage of this algorithm is that it offers an effective solution under rapidly changing atmospheric conditions. The main drawback associated with the IncCond method is that it requires complex control circuitry.

3.3. Hybrid methods

The hybrid methods are expected to track MPP more efficiently. In these methods, the control signal associated with the algorithm consists of two parts. Each part is generated based on a separate algorithmic loop. The first part is determined according to one of the simplified offline methods as a constant value, which depends on the given atmospheric conditions of the PV panel and represents the fixed steady state value. This part of the control signal is intended to follow the MPP approximately and is only required to present a fast response to the environmental variations. This part can be generated using one of the previous offline methods or simplifications thereof based on the relationship between output power characteristics and ambient. The second part of the control signal, which could be obtained based on one of the online methods involving steady state searches, represents attempts to track MPP exactly. In contrast to the first part of the control signal this part attempts to minimize the steady state error and does not require a fast response to the environmental variations. Fig. 10 provides a general description of the hybrid method. As indicated, the first part of the control signal is generated using an offline method through the set-point calculation loop, while the second part is obtained by employing an online method via the fine tuning loop.

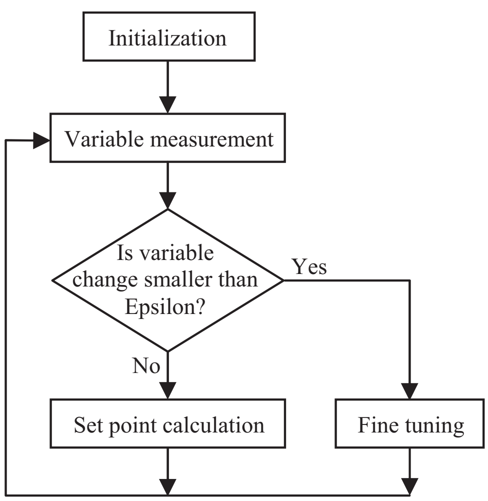

Fig. 10. General algorithm of hybrid methods.

In [69] a hybrid method consisting of two loops is proposed. In the first loop MPP is estimated based on the open circuit voltage at a constant temperature. In the second loop by applying the P&O method the exact amount of the maximum output power will be sought. In order to improve the transient and steady-state responses, the amplitude and frequency of perturbation are kept very small.

In [70,71] a hybrid method is proposed that uses an offline method to bring the operating point of the PV array close to the MPP and then uses the online IncCond approach to track the MPP with high accuracy. Through proper control of the power converter, the initial operating point is set to match a load resistance proportional to the V_{OC}/I_{SC} ratio associated with the PV array. This hybrid method also ensures that the real MPP is tracked in case multiple local maxima are present.

In [72,73] the use of fuzzy logic for implementing variable size perturbations is discussed in the context of achieving improved transient and steady state responses. The duty cycle of the power electronics converter is adjusted in order to push the operating point towards the MPP region as quickly as possible, thereby improving the transient response. Once the MPP region is reached, a modified P&O algorithm based on fuzzy logic, which is optimized for small variations around the MPP, is used. This approach results in reduced oscillations and increased power yield under the steady state conditions. In these articles each loop applies the P&O method using perturbations of different amplitude. The decision on which loop is to be implemented is determined by fuzzy logic. Use of this method along with peak current control results in an improvement in the transient response as well as a decrease in the power loss under steady state conditions [72].

Other hybrid methods are reported elsewhere [74–76]. In [74], a linear function is used to detect the location of the operating point relative to the MPP so that a perturbation of appropriate sign can be applied.

In [75], a two-loop algorithm is proposed that allows for faster tracking in the first loop and performs finer tracking in the second loop. In [76], the nonlinear equation describing the output power

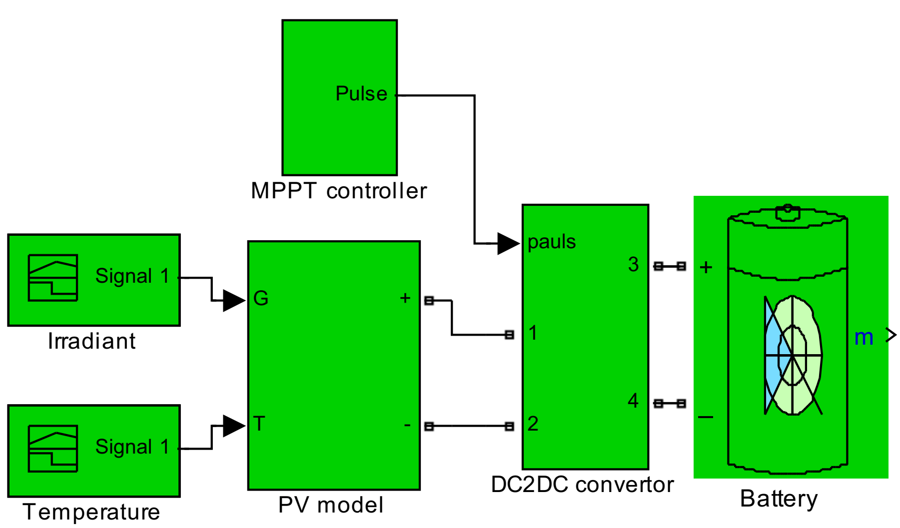

Fig. 11. The simulated system diagram.

characteristics is employed to estimate an initial operating point close to the MPP.

In [77], a hybrid analog maximum power point tracking technique is proposed which combines the offline OCV and the online P&O MPPT methods. In this method VOC, which has been measured directly, is used as the initial estimate of MPP. Power interruption to the solar array as a result of measurement of VOC occurs only once when the system is powered up. In the fine-tuning loop the P&O method is used to calculate the slope of the characteristic curves in order to track the MPP more accurately.

4. Simulation results and disscussion

In this section the PV system used in this work for simulations is introduced. Some of the MPPT methods have been compared in terms of their efficiency, dynamic response based on simulations in the Matlab/Simulink software. In addition, the characteristics of the different MPPT methods were reviewed and compared, the results of which are summarized in a Table suitable for use as a selection guide.

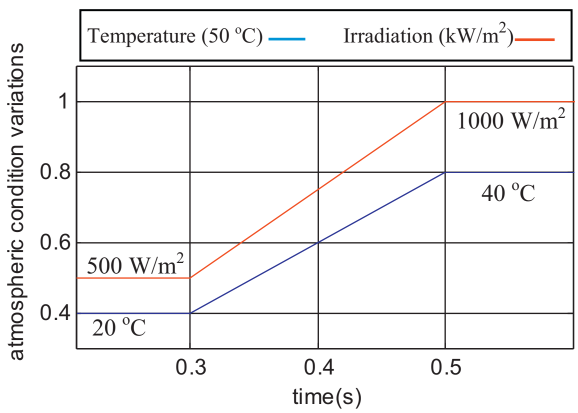

Fig. 12. Variations of irradiant and temperature.

4.1. Model description

Simulations were performed on a photovoltaic system for comparison of MPPT methods. The PV system used in the simulations is shown in Fig. 11. This system consists of a 60 W solar panel, a boost voltage converter operating at a frequency of 25 kHz, an input inductance of 820 micro Henry, an output capacitor of 100 μF, a 36 V battery used as load and a voltage regulator for the DC bus. In these simulations, the input of the converter was connected to the solar panel, the output was connected to the battery and the control signal generated by each MPPT method fed the boost converter switch. The system was simulated in MATLAB/SIMULINK environment.

4.2. Simulation results

A number of MPPT methods are implemented in Matlab/Simulink software environment as a controller to study and compare the dynamic response of the PV system. All simulations are performed under variations in irradiance and temperature as depicted in Fig. 12.

Among the offline methods, the OCV method, the SCC method and the ANN method have been simulated the results of which have been depicted in Fig. 13. As shown in Fig. 13a, the ANN method tracks the MPP quite accurately under variations in irradiance. The OCV and SCC methods, however, follow the MPP

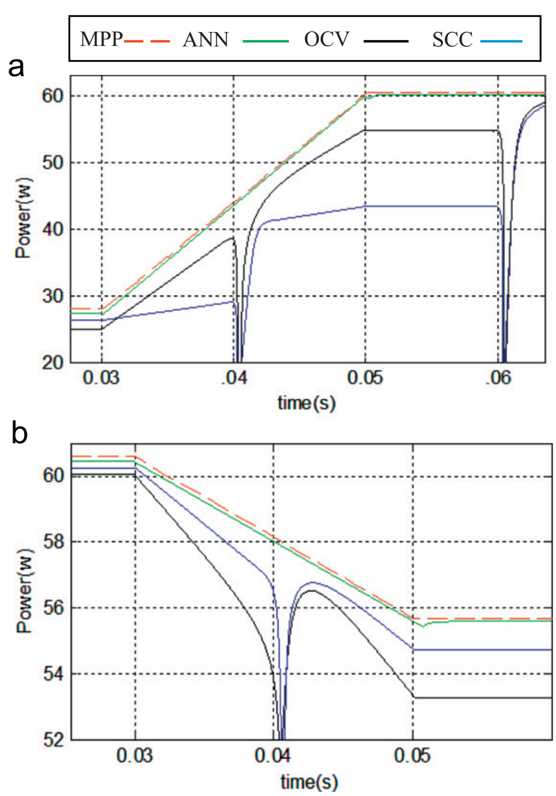

Fig. 13. The output power of PV in variations of (a) irradiance, (b) temperature.

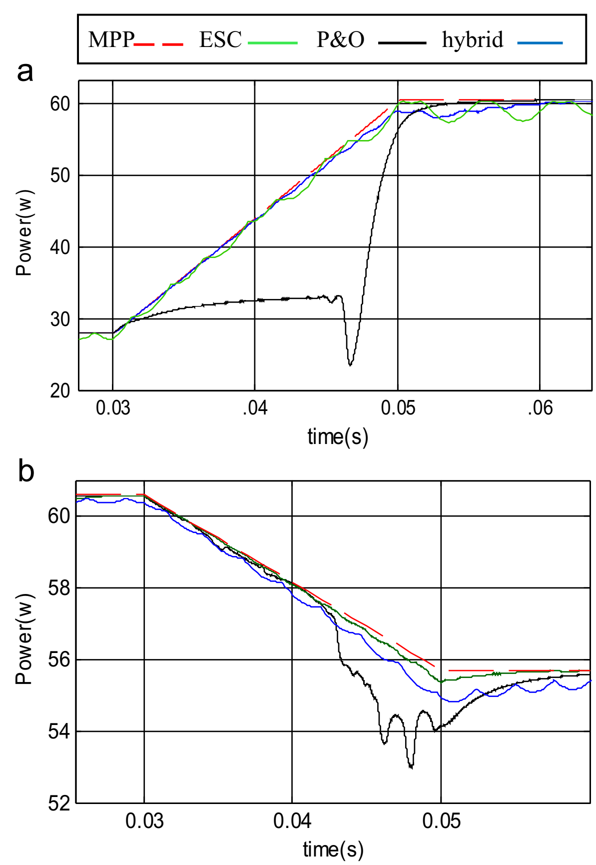

Fig. 14. The output power of PV in variations of (a) irradiance, (b) temperature.

Table 1
Major characteristics of MPPT techniques.

MPPT method	Type	Complexity	Digital or analog	Convergence speed	Sensed parameters	Prior training	Efficiency
Open circuit voltage	Offline	Low	Both	Medium	Voltage	Yes	Low (=86%)
Short circuit current	Offline	Medium	Both	Medium	current	Yes	Low (=89%)
Artificial neural networks	Offline	High	Digital	Fast	Depends	Yes	High (=98%)
Fuzzy logic	Offline	High	Digital	Fast	Depends	Yes	High
P&O (fixed perturbation size)	Online	Low	Both	Low	Voltage and current	No	Low
P&O (variable perturbation size)	Online	Medium	Digital	Fast	Voltage and current	No	High (=96%)
ESC	Online	Medium	Both	Fast	Voltage and current	No	High (=97%)
IncCond	Online	Medium	Digital	Depends	Voltage and current	No	High
Method of [69]	Hybrid	Medium	Both	Fast	Voltage, current and temperature	No	High (=98%)

approximately and their accuracy suffers as a result of power interruptions. As mentioned above, the interruption in power is associated with measurement of open circuit voltage and short circuit current in the OCV and SCC methods respectively. While the offline methods considered exhibit a similar performance in terms of accuracy under variations in temperature, the SCC method tracks the MPP more accurately as compared to the OCV method (Fig. 13b).

Simulations were also performed based on the online methods of P&O and ESC as well as the hybrid method of [69], the results of which have been illustrated in Fig. 14. Fig. 14, indicates that while the P&O method fails to track the MPP for fast variations in the irradiance and temperature, the ESC and the hybrid method follow the MPP reasonably well.

4.3. Discussion

The MPPT methods are compared in terms of dynamic response, efficiency, and implementation schemes.

4.3.1. Dynamic response

The simulations results indicate that the offline ANN method, the online ESC method as well as the hybrid method of [69], are all able to the track the MPP relatively accurately. On the other hand, the P&O online method which uses a variable perturbation size exhibits a poor dynamic response, and is unable to track MPP. The offline methods OCV and SCC also have poor dynamic responses resulting from power interruptions during measurements.

4.3.2. Efficiency

In special applications employing PV panels such as the power supply used in satellites and spacecrafts as well as in large scale PV power plants the efficiency of the MPPT method constitutes the most important initial consideration. The efficiency of the MPPT methods was assessed qualitatively based on simulations by considering the steady state response of the system. The efficiency can also be quantified using the following equation [78]:

$$\eta_T = \frac{1}{n}\sum_{i=0}^{n}\frac{P_i}{P_{\max,i}} = \frac{1}{n}\sum_{i=0}^{n}1-\frac{P_l}{P_{\max,i}} \tag{9}$$

where, P_i is the solar panel power, $P_{\max,i}$ is the maximum solar panel power, $P_l(=P_{\max,i}-P_i)$ is the wasted power, and n is the number of samples.

The review in this work indicated that in terms of efficiency the MPPT methods considered can be ranked as follows: (1) hybrid, (2) ANN, (3) FL-based controller, (4) P&O (variable perturbation size), (5) IncCond, (6) ESC. This ranking is also confirmed based on our simulations for the hybrid, ANN, P&O and ESC methods (Figs. 13 and 14). Furthermore, the simulation results indicate, the OCV and the SCC methods exhibit low efficiency even if optimum constant (k) values are selected.

4.3.3. Implementation

Considerations relating to implementation of MPPT methods include the relative ease of implementation, costs as well as hardware requirements. These considerations, however, influence one another.

The ease of implementation has an important influence on the decision to select a given MPPT technique. Consideration of ease, however, greatly depends on the end users' knowledge and experience.

It is hard to quantify the monetary costs associated with each MPPT technique unless the method is implemented in practice. Whether the technique is an analog or a digital implementation, whether it requires software and programming, as well as the number of sensors required for implementation are important factors influencing the overall costs. Analog implementation is generally cheaper than its digital counterpart, which normally requires a microcontroller and the necessary programming.

In terms of overall implementation considerations the MPPT methods can be ranked as follows: (1) OCV, (2) SCC, (3) P&O (with fixed perturbation size), (4) hybrid methods, (5) P&O (variable perturbation size), (6) IncCond, (7)ESC, (8) ANN, (9) FL-based method.

The major characteristics of the MPPT techniques have been summarized and presented as a selection guide in Table 1.

5. Conclusion

In this review, several MPPT methods have been surveyed and their advantages and disadvantages were compared based on simulations. These methods have been classified into three categories: off-line, online and hybrid methods. This classification is based on the approach used for generation of the control signal as well as the PV system behavior around the steady state conditions. Different MPPT methods are compared based on simulations in the Matlab/Simulink environment in terms of the dynamic response of the PV system, attainable efficiency, and implementation considerations. The implementation considerations were discussed in terms of the relative ease of implementation, costs and hardware requirements.

The results indicate that the implementation considerations influence both the efficiency and the dynamic response of the system. In particular, methods with low cost, low hardware requirements and easy implementation exhibit relatively poor dynamic response as well as efficiency. However, under relatively equal implementation conditions the hybrid methods have a better performance. Finally, a table is provided which can serve as a guide for selection of the appropriate MPPT method for specific PV system applications.

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